A Multi-Objective Perspective to

Satellite Design and Reliability Optimization

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Abstract

Development of a communication satellite project is highly complicated and expensive which costs a few hundred million dollars depending on the mission in space. Once a satellite is launched into orbit, it has to operate in harsh environmental conditions including radiation, solar activity, meteorites, and extreme weather patterns. Since there is no possibility of physical maintenance intervention in space, reliability is a critical attribute for all space and satellite projects. Therefore, the redundancy philosophy and reliability measures are taken into account in the design phase of a satellite to prevent the loss of functionality in case of a failure in orbit. This study aims to optimize the payload design of a communication satellite by considering the system's reliability, power consumption and cost simultaneously. Since these objectives are conflicting in their nature, a multi-objective optimization approach is proposed. We offer a systematic approach to the satellite design by determining the best redundancy strategy considering contradictory objectives and onboard constraints in the multibillion-dollar satellite industry. The proposed approach promotes trade-offs and sensitivity analyses between cost, power consumption and system reliability in the early design phase of satellites using Compromise Programming. By using different sets of weights for the objectives in our model, it is possible to address different types of satellites depending on their mission and priorities. Because of the NP-Hard characteristics of the reliability optimization problem and the nonlinear equation in the offered model, the Simulated Annealing algorithm is utilized to solve the problem. As a case analysis, the implementation is carried out on the design of a communication satellite system with active hot-standby and warm-standby onboard redundancy schemes. Results reveal that huge savings in million dollars can be attained as a result of approximately 5% reduction in reliability figure.

Keywords: Multi-Objective Optimization, Satellite Design, Satellite Reliability Optimization, Redundancy Allocation Problem, Compromise Programming, Simulated Annealing

Introduction

Reliability-related topics have attracted significant interest in recent years as high-tech systems become increasingly sophisticated with cutting-edge technological and scientific advancements. In this respect, reliability is considered an indispensable attribute for space systems and one of the most important objectives in satellite design and its optimization (Castet & H.Saleh, 2009).

Reliability of a system is defined as the ability of a system or component to perform its functions under defined conditions and at the desired performance for a specified period of time (O'Connor & Kleyner, 2012) (Elsayed, 2012). The reliability of a satellite system renders a critical role in achieving desired expectations on space projects through forefront technologies where accessibility is limited once the satellite reaches its orbit.

Satellite systems are classified concerning their application areas such as Communication, Earth Observation Remote Sensing, Navigation and Research satellites. Another classification of the satellites is done according to their orbits as; Low Earth Orbit (LEO), Medium Earth Orbit (MEO), Geosynchronous Earth Orbit (GEO), and Elliptical Orbit satellites. The masses of satellites vary from less than a kilogram to several tones spanning a wide range. The service lifetimes of the satellites vary from a couple of years for small ones and up to 15 years for typical geostationary communication satellites, depending upon their mission. According to the Union of Concerned Scientists (UCS) database (Database, 2022), which keeps a record of the operational satellites, there are more than 5,465 operational satellites currently in orbit by May 1, 2022, and it is expected that 17,000 satellites will be launched over the next decade (Euroconsult, 2022). If a critical unit fails in a satellite during its anticipated lifetime in orbit, the satellite will be partially and completely dysfunctional beyond repair; therefore, the optimization of system design and reliability is essential and needed to be realized for each type of the above-mentioned satellite. The reliability optimization becomes more complex for large systems since several subsystems involve a relatively high number of components and different strategies of redundancy.

This study has focused on communication satellites since they are the heaviest and the most complicated type of satellites. Arthur C. Clarke's 1945 article in the Wireless World magazine brought the concept of communication satellites (Evans, 1999). As an extension of intercontinental cable systems and in applications such as data transmission and television/radio broadcasting, communication satellites are essential where terrestrial lines cannot reach the desired location in the world. In television broadcasting, the signals transmitted from the station to the satellite are disseminated to vast tracts after their frequencies are modified and signal levels are amplified (Braun, 2012). These satellites are situated in geosynchronous orbit, which is about 35,786 kilometers above the Earth's surface and rotates at the same speed as the globe.

The building up of a communication satellite project is highly complicated and expensive which costs a few hundred million dollars depending on their mission in space. Besides these satellites are placed into space by launch services that charge significant amounts per their weight. After satellites are launched, there is no possibility of physical intervention from the ground in case of any malfunction of a unit in the harsh space environment such as radiation, high-temperature differences, solar activities, meteorites, etc. with potential threats to the satellite reliability. An established strategy for preventing loss of functionality is the use of redundancy philosophy and reliability approaches considered during the design phase (Rausand & Hoyland , 2004).

Reliability is increased by each additional piece of equipment that is employed onboard since it can be utilized in the event of a failure. As a result, the entire system becomes more expensive and complex while also requiring more volume, mass, and power resources which are rather limited in space vehicles. By maximizing the system's redundancy and reliability through a comprehensive methodology, it is possible to develop a satellite that is both economical and resource-wise efficient.

To the best of our knowledge, current industrial practices in satellite design involve iterative attempts to determine the redundancy strategy and number of redundant units onboard concerning the customer reliability requirements. Generally, the customer reliability requirement for a satellite is driven by the availability analysis of the specific mission (Birolini, 2013). There are guidelines for reliability design and reliability prediction in the Military Handbook of the USA Department of Defense which give substantial instructions (MIL-HDBK-338B, 1998), (MIL-HDBK-217F, 1991) , and also in the European Cooperation for Space Standardization (ECSS) documents (ECSS, 2011). There are also a few commercial software in the industry for modeling reliability block diagrams and reliability analysis such as PTC Windchill Quality Solution in quality and reliability management (PTC, 2022). Nevertheless, they do allow system-level optimization. Even though not publicly available and unveiled in the literature, the leading industrial companies might have their internal toolset for system and reliability optimization. Apparently, without a methodical and suitable technique, the determination of the best redundancy strategy and an optimal number of redundant units in each subsystem of a satellite is achieved by a trial-and-error approach trying to satisfy the customer reliability requirements. Such an approach involves iterative attempts to satisfy the reliability requirements with a minimum number of equipment thereby trying to keep the cost to a minimum. However, there are significant tradeoffs between system reliability, system cost and limited onboard resources such as available volume, power, and thermal dissipation parameters. Unless a systematic, multi-objective approach is employed, it will be quite difficult to uncover the nature of the trade-offs and find a true multi-objective optimum. At best, the trial-and-error approach will produce a near-optimal solution.

This study aims to optimize the payload design of a communication satellite by considering the system's reliability, power consumption, and cost simultaneously which are naturally conflicting. Therefore, we propose a Multi-Objective Optimization (MOO) approach. MOO ensures the process of optimizing multiple objectives simultaneously, where each objective may have conflicting requirements. Unlike Single-Objective Optimization (SOO), where the goal is to minimize or maximize a single objective function, MOO seeks to find a set of trade-off solutions that simultaneously satisfy multiple objectives. These trade-off solutions are often referred to as the Pareto front, which represents the set of non-dominated solutions. In satellite design, the maximization of satellite reliability by accommodating space-qualified redundant units onboard entails an increase in power consumption due to the active redundant units, which in turn raises the satellite cost. MOO approaches are well suited for resolving such conflicts in optimization problems.

The objective function involves maximization of system reliability and minimization of cost and power consumption of units considering an active and warm standby redundancy strategy. In the model, several constraints typically imposed by the customer or the system design architect are also taken into account. Even though there are several studies with several objective functions utilized for multi-objective redundancy-reliability optimization of complex systems in the literature; the combination of reliability, cost and power consumption is not considered heretofore.

In the frame of this study, we use the Compromise Programming (CP) method as the MOO method to obtain Pareto-efficient subsets from the feasible solutions. The CP method does not rely on assumptions of the traditional utility theory (Romer & Rehman, 2003). CP utilizes a distance function to reach the ideal or "utopian" solution as close as possible. The distance function is not utilized in a geometric sense; it is rather a proxy measure to be tailored to the decision maker's preferences. The weights appointed to each objective as a measure of relative importance allow diversification of our problem. By different sets of weights, it is possible to address different types of satellites depending upon their mission and priorities. In this study, two sets of weight are defined by expert judgments in the model: one for commercial satellite domain, called Satellite-A, and another for governmental/military mission at defense grade, called Satellite-B as explained in Section 5.

Only a few studies focus on reliability allocation models for Satellites. (Hassan & Crossley, 2008) presented a genetic method with Monte Carlo sampling for probabilistic reliability-based design optimization of satellite systems. In (Castet & H.Saleh, 2009), the maximum likelihood estimation approach is used to investigate the reliability of satellite subsystems using Weibull distributions. (Nefes, Demirel,, Ertok, & Sen, 2018) examined the power amplifier redundancy system of a communication satellite payload module using an analytical approach under various failure rates. (Mansouri & Alem-Tabriz, 2022) proposed a mixed integer nonlinear model for the satellite attitude determination and control system. Recently, (Tetik, Daş, & Birgören, 2024) proposed an integer nonlinear model to minimize the cost of a communication satellite using a two phased approach.

To the best of our knowledge, there is no study in the literature considering the satellite design problem using multi-objectives from the perspective of reliability and redundancy optimization. In this study, we propose an integer nonlinear multi-objective programming problem. The proposed satellite-specific model is dealt with CP and SA due to its multi-objective, nonlinear and NP-Hard nature. The use of this model during the satellite design offers a systematic approach that could also be implemented for non-repairable complex systems in diverse industrial domains, encompassing chemical plants, nuclear systems, power generation facilities, oil and gas refineries, aerospace industries, and large-scale compound manufacturing plants. It also facilitates critical trade-offs between objectives to be analyzed, and enhances reliability in satellite systems, incorporating costly redundant active and warm standby units. The rest of the article is arranged as follows. Section 2 includes a literature survey on Reliability and Redundancy Optimization. In Section 3, the MOO problem for a communication satellite is described. The CP method and the SA algorithm are discussed in Sections 4 and 5, respectively. Section 6 illustrates how the model works on case study data obtained from the satellite industry for a rather large-size communication satellite consisting of 58 nominal payload channels. Finally, in Section 7 conclusions are presented.

1. Reliability–Redundancy Optimization

There are many studies on reliability optimization of complex systems in the literature. Kuo and Prasad (Kuo & Prasad, 2000) offer literature survey for earlier studies of system reliability optimization. By concentrating mostly on studies published after the year 2000, (Soltani, 2014) provides a more recent survey on models and approaches for reliability optimization problems, encompassing reliability and redundancy allocation approaches.

In general, there are various reliability optimization problems in the literature; the Redundancy Allocation Problem (RAP), Reliability Allocation (ReAP) and the Reliability–Redundancy Allocation Problem (RRAP). In RAPs, the main objective is to find the best combination of components and levels of redundancy that together meet reliability and cost requirements to satisfy the system constraints (Coit and Smith, 1996). ReAP, on the other hand, seeks to find the best allocation of reliability to components or subsystems of a system to maximize the overall system reliability or minimize the system cost under specified constraints (Twum, 1996, Thesis). Whereas RRAPs are a combination of these two problems. Therefore, RRAPs engage in the optimization of component reliabilities concurrently with redundancy levels (Wanga, Linb, Fua, Luoa, & Chena, 2020). A discussion of the literature on these problems can be found in (Kuo & Prasad, 2000) and (Kuo W. , Prasad, Tillman, & Hwang, 2001)

While determining redundant units in RAPs and RRAPs, there are there basic strategies according to the operations modes: (i) active redundancy, (ii) standby redundancy and (iii) mixed redundancy (Kim & Kim, 2017), (Heungseob, 2017). In the active redundancy strategy, the redundant units are in power-on mode since the beginning of the mission. Whereas in the standby redundancy strategy, there are three modes called (a) hot standby, (b) cold standby, and (c) warm standby. In the hot standby strategy, entire units are in active operating state where the load is distributed simultaneously to all units and the failure rate of the hot standby component is the same as the main unit. In the warm standby strategy, the redundant units are in online state and do not share the load. In the warm standby system, the failure rate of the standby unit is less than that of the main unit. In the cold standby strategy, all of the redundant components are in offline state and need to be powered up and switched to the operating mode upon request (Elsayed, 2012). In the mixed redundancy strategy case, both active and standby units are utilized simultaneously in a combinatorial way. In satellite system architecture, generally hot standby and warm standby strategies are utilized depending on the operations mode and criticality of the subsystems. In this study, we consider hot and warm standby strategies for satellite design.

Reliability optimization design problems are known as NP-hard (Chern, 1992). The RAPs and RRAPs have been solved in the literature by several methods such as column generation (Zia, 2010) interval optimization (Munoz & Pierre, 2004), differential dynamic programming method (Ng & Sancho, 2001), (Yalaoui, Châtelet, & Chu, 2005) and exact methods such as Lagrangian relaxation and dynamic programming (Ashrafi & Berman, 1992), branch-and-bound (Ha & Kuo, 2006), (Caserta & Voß, 2015) or cutting plane methods that are based on a linear integer programming relaxation and successive application of the simplex algorithm (Coit & Liu, 2000), lexicographic search and upper-bound based algorithm (Prasad & Kuo, 2000), improved surrogate constraint method (Onishi, James, & Nakagawa, 2007), functional evaluations and a limited search close to the boundary of resources-based mixed integer programming algorithm (Misra & Sharma, 1991).

Due to the NP-Hard characteristics of reliability optimization problems, various meta-heuristic algorithms such as SA; (Atiqullah & Rao, 1993), (Wattanapongsakorn & Levitan, 2001), (Shelokar, Jayaraman, & Kulkarni, 2002), (Kim, Bae, & Park, 2004), (Kim, Bae, & Park, 2006), Genetic Algorithms (GA); (Coit & Smith, 1996), (Deeter & Smith, 1997), (Busacca, Marseguerra, & Zio, 2001), (Lee, Gen, & Kuo, 2002), (Elegbede & Adjallah, 2003), (Suman, 2003), (Konak, Coit, & Smith, 2006), (Roy, Mahapatra, & Mahapatra, 2014), Simplified Swarm Optimization (SSO); (Lai & Yeh, 2016), Particle Swarm Optimization (PSO) (Huang, 2015), (Kumar, Pant, Ram, & Singh, 2017) (Ouyang, Liu, Ruan, & Jiang, 2019), (Li, Chi, & Yu, 2022)), Bee Colony Algorithm (BCO) ((Yeh & Hsieh, 2011), (Zhang, Li, & Chen, 2021)), Ant Colony Optimization (ACO) ((Nahas & Nourelfath, 2005), (Ahmadizar & Soltanpanah, 2011)) Tabu Search (TS); (Kulturel-Konak, Smith, & Coit, 2003), (Jang & Kim, 2011) are proposed in the literature both for single and multi-objective problems. For a comprehensive classification and survey about past studies of reliability optimization models and solution approaches, the interested reader is referred to the review studies published by (Kuo & Prasad, 2000), (Kuo W. , Prasad, Tillman, & Hwang, 2001), (Kuo & Wan, 2007) Twum and Aspinwall, Soltani (Twum & Aspinwall, 2013) and (Devi, Garg, & Garg, 2023).

In this study, we offer an integer multi-objective non-linear model to solve the RAP in the design phase of a communication satellite. Our aim is to optimize the payload design of a communication satellite by considering the system's reliability, power consumption and cost simultaneously by means of optimizing the number of warm and hot standby payload channels. To solve the proposed model, we use CP and SA together. As it is clear from the above discussion the CP method as a MOO method along with the SA algorithm as a Meta-Heuristic approach has not been used in the RAP studies in the literature.

2. A Multi-Objective Optimization Model for a Communication Satellite

In the MOO model of a communication satellite, several objectives could be considered such as cost, volume and weight of the satellite, power consumption of the units and reliability of the system. The specific objectives that are considered will depend on the requirements of the communication satellite and the goals of the design process.

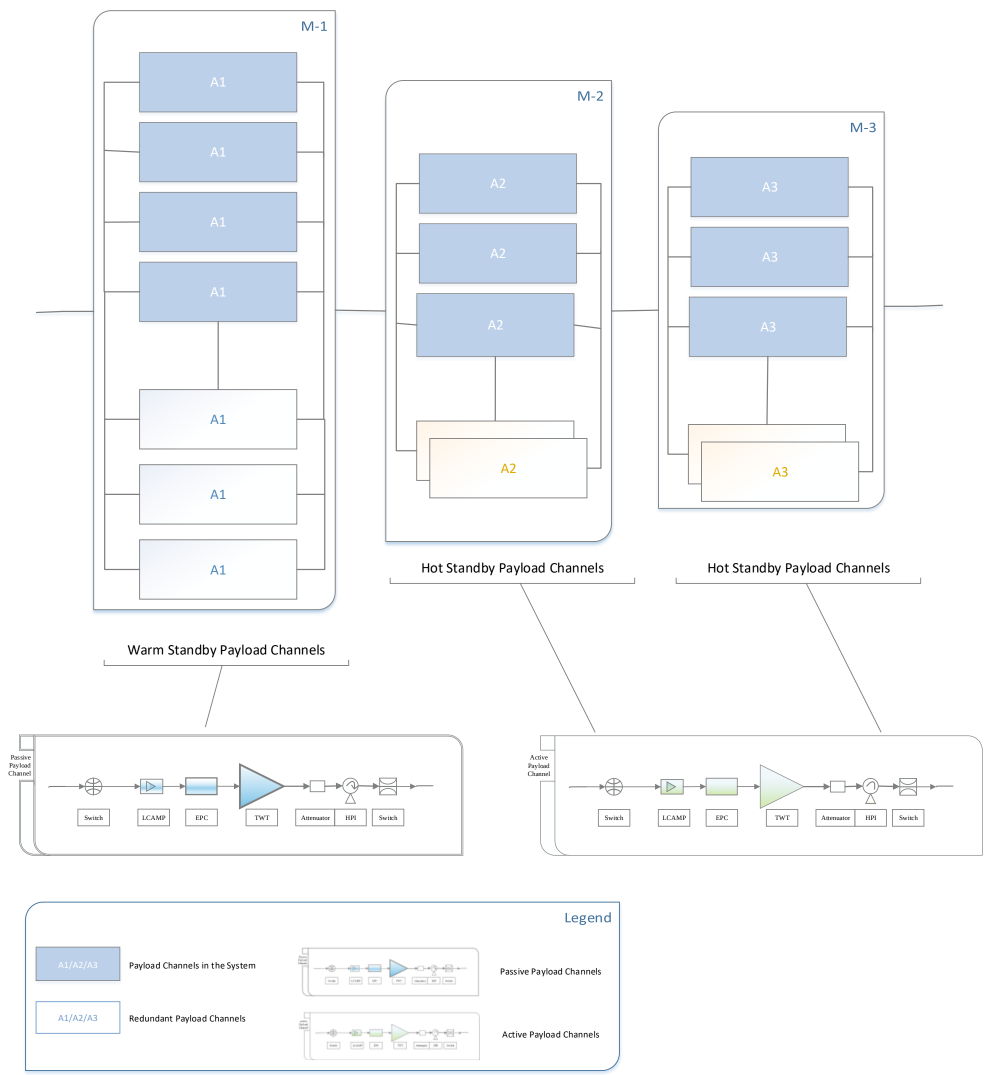
A typical communication satellite is composed of a platform (or service) module, which includes multiple subsystems and supports the mission module and a communication payload module (or communication modules including antennas and repeater subsystems). To meet the criteria for system-level reliability, each subsystem has equipment chains connected in parallel in accordance with an integrated redundancy scheme. The repeater is comprised of a set of electronic components that process the transmission signals in a wide variety of ways. It has a series of channels (also known as transponders) each of which is specifically assigned to a section of the payload frequency band (Maral & Bousquet, 2009).

In a communication satellite architecture, the Attitude and Control Subsystem (AOCS), Satellite Command and Control Subsystem (SCS), Electrical Power Subsystem (EPS), Data Handling Subsystem (DHS), Propulsion Subsystem (PS), Thermal Control Subsystem (TCS), Structural Subsystem (SS), and Telemetry, Telecommand and Ranging Subsystem (TTCR) are the subsystems of the main platform module (J. Larson & R. Wertz, 1999). These subsystems are excluded from the study due to the limited opportunity for redundancy allocation enhancement; in general, one-to-one redundancy is ensured by the spare equipment provided in the design architecture.

Notwithstanding the above, the communication payload module has a substantial number of active components with elevated failure rates as well as relatively more intensive power consumption and heat dissipation. The payload subsystem employs a significantly larger number of equipment as compared to the platform subsystems (AOCS, SCS, EPS, DHS, etc.). Therefore, it is difficult to sustain one-to-one redundancy in the payload subsystem whereas the redundancy plan is provided by means of a spare pool in case any equipment malfunctions in other subsystem. Figure 1 depicts the reliability block diagram for the communication satellite payload module under consideration in this study, which consists of three subsystems in a $k\ out\ of\ n\ (k{:}n)$ configuration. A $k\ out\ of\ n$ configuration is a design where the appropriate operation of any k or more components of the system ($k \leq n$) guarantees the proper functioning of the entire system (Jin, 2018).

The MOO model aims to optimize the number of warm and hot standby payload channels while considering the system's reliability, power consumption and cost objectives simultaneously, the resulting model is an integer nonlinear multi-objective programming model. The parameters of the model are the cost, power consumption and reliability figures of equipment and associated redundancy strategies. The key constraints are; minimum reliability requirements for each subsystem and system, maximum number of redundant units in the system and onboard power consumption limitations.

In more detail, the model optimizes the number of warm standby payload channels in the first payload mission (called M-1 in Figure 1), and optimizes the numbers of active hot standby payload channels in the second and third payload missions (called M-2 and M-3 in Figure 1). Within this context, the contribution of the rest of the platform subsystem is considered as a constant value in the calculation of the system-level reliability calculations due to the confined equipment configurations. Before introducing our model in detail, we provide a discussion on how to compute reliability for active and passive redundant systems.



s_{i_1} s_{i_2} s_{i_3}

$k_1 : n_1\,(k_1 + x_{i_1})$ $\quad$ $k_2 : n_2\,(k_2 + x_{i_2})$ $\quad$ $k_3 : n_3\,(k_3 + x_{i_3})$

Figure 1: k out of n Satellite Subsystems Reliability Block Diagram

In $k\!:\!n$ active hot standby redundant systems; the reliability of a system is modeled by the binomial distribution and can be expressed in the following form (Jin, 2018);

$$R(t) = \sum_{i=\mathrm{k}}^{n} \binom{n}{i} \left(1 - R(t)\right)^{n-i} \left(R(t)\right)^{i} \tag{1}$$

where, $R(t) = e^{-\lambda t}$ is the reliability of a system in terms of constant failure rate λ (exponentially distributed lifetimes) that is assumed throughout the service life of a satellite (MIL-HDBK-338B, 1998), given that the components used are identical and independent, $R_1(t) = R_2(t) = \cdots = R_n(t)$.

In k:n warm standby passive redundant systems, (She & Pecht, 1992) provided a closed-form expression for the system reliability function as given in Equation (2), assuming that all components are independent and identically distributed, and the lifetime of each component follows an exponential distribution with the failure rate parameter λ_o for active operational equipment and failure rate parameter λ_d for stationary equipment (Kuo & Zuo, 2003).

$$R(t) = \frac{1}{(n-k)!\,{\lambda_d}^{n-k}} \sum_{i=0}^{n-k} (-1)^i \binom{n-k}{i} \left[\prod_{j=0, j\neq i}^{n-k} (k\lambda_o + j\lambda_d) \right] e^{-(k\lambda_o + i\lambda_d)t} \tag{2}$$

When $\lambda_d = \lambda_o = \lambda$, the active redundant system formula given in Equation (1) can be obtained from the formula given in Equation (2). In our study, Equation (2) is utilized for M-1 Subsystem whereas Equation (1) is utilized for M-2 and M-3 Subsystems.

To solve the RAP for a communication satellite, a Multi-Objective Optimization Model (called MOOM) has been developed as described in Equation (3) to Equation (10).

Parameters:

R_{sys_min} : $minimum\ required\ reliability\ value\ of\ system$

R_i : $reliability\ of\ subsystem\ i\ including\ redundant\ equipment$

R_{i_min} : $minimum\ required\ reliability\ value\ of\ subsystem\ i$

c_i : $cost\ of\ redundant\ equipment\ i$

$n_{\max}$: *maximum number of redundant equipment in the system*

P_i : *power consumption of equipment i (Watt),*

P_{red} : *maximum allowable power consumption of redundant equipment (Watt),*

n_i : *total number of equipment in subsystem i*

k_i : *minimum number of equipment required for subsystem i*

s : *number of subsystems*

Decision Variables:

$x_i =$: *number of redundant equipment in subsystem i*

MOOM:

$$\min g_1(x) = \sum_{i=1}^{s} x_i\, c_i \tag{3}$$

$$\min g_2(x) = \sum_{i=1}^{s} x_i\, P_i \tag{4}$$

$$\max g_3(x) = \prod_{i=1}^{s} \sum_{j=k_i}^{k_i+x_i} \binom{k_i + x_i}{k_i} R_i^j (1 - R_i)^{k_i+x_i-j} \tag{5}$$

st.

$$\prod_{i=1}^{s} \sum_{j=k_i}^{k_i+x_i} \binom{k_i + x_i}{k_i} R_i^j (1 - R_i)^{k_i+x_i-j} \geq R_{\text{sys\_min}} \tag{6}$$

$$\sum_{i=1}^{s} x_i \leq n_{\max} \tag{7}$$

$$\sum_{j=k_i}^{k_i+x_i} \binom{k_i + x_i}{k_i} R_i^j (1 - R_i)^{k_i+x_i-j} \geq R_{\text{i\_min}}, \qquad \forall i \tag{8}$$

$$\sum_{i=1}^{s} x_i \, P_i \leq P_{red} \tag{9}$$

$$x_i \geq 0 \; and \; integer, \qquad \forall i \tag{10}$$

The model aims to minimize the cost and power consumption of the system while maximizing the system reliability, which are expressed in Equation (3) to (5). Equation (6) ensures that the system reliability is greater than the minimum required value. Equation (7) provides the allowable limit for the number of spare equipment in the system. Equation (8) ascertains that each subsystem's reliability is greater than the minimum specified value. Equation (9) expresses the power supplies constraint for spare equipment. Finally, Equation (10) ensures that the number of redundant equipment is positive integer valued. To solve this model, we use the CP approach that will be introduced in the next section.

3. Compromise Programming

CP, also known as the Global Criterion Method, is one of the approaches utilized in the literature of MOO problems. CP is developed by (Zeleny, 1973), (Yu, 1973), (Zeleny, 1974), (Zeleny, 1982), and (Yu, 1985) that finds the best solution by minimizing the distance between alternatives and a reference point, which is also called the ideal or utopian point (Escobar & Moreno-Jimenez, 1997).

Weighted-sum (WS) is the most common approach to multi-objective optimization (Marler & Arora, 2004). However, it has been mathematically proven that CP is superior to the WS in locating the efficient solutions, or the so-called Pareto points (Chen, Wiecek, & Zhang, 1998). Also, CP can also be considered as a generalized version of WS: When the parameter *p* in CP is set to 1, as will be discussed later, it reduces to WS. Because of its superiority and generality, CP is preferred as the MOO method in this study.

CP has been employed to solve various problems in the literature. (Abrishamchi, Ebrahimian, M, & A., 2005) used CP as a ranking method to satisfy potable water consumers. (MJ & SP, 2000), (Zarghami, 2006) and (Fattahi & Fayyaz, 2010) also utilized the CP for water management research. (Poff, Tecle, Neary, & Geils, 2021) have implemented CP as a spatio-temporal Multi-Objective Decision-Making (MODM) method to solve a forest ecosystem's land management planning process involving multiple interests. (Ngo, et al., 2022) proposed a CP based approach to the Vehicle Routing Problem (VRP). In the study of (Ngo S. T., 2021), the lecturer assignment problem is solved by the CP formulation. (Osmani, Kochov, & Ilazi, 2021) considered Compromised Programming to find solutions among different conflicting objectives such as minimizing the cost and CO_2 emissions in the electricity generation system.

CP method has been also implemented in the area of RAP in the studies of (Mahapatra, 2009), the (Sadjadi, Tofigh, & Soltani, 2014) and (Soltani, Sadjadi, & Tavakkoli-Moghaddam, 2015). (Mahapatra, 2009) considered a series-parallel system to find out the number of redundant components that will maximize the reliability and the entropy of the system. (Sadjadi, Tofigh, & Soltani, 2014) studied a RAP with serial parallel structures and determined the redundancy strategy and component type for the given system. (Soltani, Sadjadi, & Tavakkoli-Moghaddam, 2015) offered a model which maximizes the reliability and the entropy in distribution of the weights of components and minimizes the nonlinear cost of the system simultaneously. Minimization of power consumption has never been considered as an objective function in the RAP literature while it is an essential objective along with maximization of system reliability and minimization of cost.

Consider a MOO problem described as follows (Marler & Arora, 2004):

$$\min \quad F(x) = [F_1(x), F_2(x), \dots, F_k(x)\ ]^T \tag{11}$$

$$\text{s.t.} \quad g_j(x) \leq 0,\ j = 1,2,\dots,m \tag{12}$$

$$h_l(x) = 0, \qquad l = 1,2,\dots,e \tag{13}$$

where the number of objective functions is k, the number of inequality constraints is m, and the number of equality constraints is e. A compromise solution is a single solution which is as close as possible to the utopian/ideal point (Marler & Arora, 2004). The ideal point F^0 is an unattainable point for each i , $F_i^0 = minimum\ \{Fi(x)\ |\ x \epsilon X\}$.

The basic idea of CP is to seek a solution set as close to the ideal point according to the decision maker's preferences as possible. To attain this goal a distance-based function is utilized in the analysis (Romer & Rehman, 2003). The difference between the ideal point and the solution found by the method represents the degree of compromise made between the conflicting objectives. The smaller this difference, the closer the solution to the ideal solution.

The CP approach does not typically require explicit articulation of preferences. The decision maker simply needs to provide information about the conflicting objectives and their constraints. The approach uses a mathematical model to represent the conflicting objectives and finds a solution that is a compromise between them. The method then finds a solution that balances the conflicting objectives in a way that is consistent with the constraints. The solution found by the method represents the trade-off between the conflicting objectives and can be used to support decision making in situations where it is difficult to prioritize the objectives.

The L_p distance, also known as the L_p norm, is a measure of the distance between two vectors in a multi-dimensional space. Suppose we have two solutions x^1 and x^2 then the distance between these two solutions can be expressed as:

$$L_p = \left[\sum_{j=1}^{n} \left|x_j^1 - x_j^2\right|^p\right]^{1/p} \tag{14}$$

In CP, it is often used as a measure of the deviation between the actual and desired values of an objective function. The L_p distance is defined as the p^{th} root of the sum of the absolute differences between the elements of two vectors raised to the power of p. The value of p determines the type of L_p distance, with different values of p corresponding to different measures of distance. For instance; L_1 distance (also known as the Manhattan distance or taxicab distance) corresponds to $p = 1$. It is the sum of the absolute differences between the elements of the two vectors. L_2 distance (also known as the Euclidean distance) corresponds to $p = 2$. It is the square root of the sum of the squares of the differences between the elements of the two vectors. L_∞ distance (also known as the Chebyshev distance or maximum norm) corresponds to $p = \infty$. It is the maximum of the absolute differences between the elements of the two vectors. The L_p distance is then minimized or maximized as part of the optimization process to find the trade-off solutions that satisfy multiple conflicting objectives.

In the CP methodology, Equation (15) is used to measure the L_p distance of each solution to the ideal point which can be considered as a proxy measure for the decision maker: Since we deal with multiple objectives, the distance parameter is computed by scaling as presented in Eq. (15);

$$L_p(x) = \left[\sum_{i=1}^{l} w_i^p \left|\frac{f_i^* - f_i(x)}{f_i^* - f_i'}\right|^p\right]^{1/p} \tag{15}$$

where f_i^* and f_i' denote ideal(utopian) and anti-ideal (nadir) values of respective criterion $i \epsilon I$ which correspond the minimum and maximum objective value of $f_i(x)$. The ideal and anti-ideal points indicate possible range of the objective values of all the criteria over the Pareto set. The ideal point is defined as the best possible solution in terms of all of the objectives which represents the maximum value of each objective. Similarly, the anti-ideal point in CP is a point that represents the worst possible solution for a problem considering all the conflicting objectives (Romer & Rehman, 2003), (Ehrgott & Tenfelde-Podehl, 2020). The parameters w_i are the weights representing the relative importance of the i^{th}objective according to the decision maker. The exponential parameter of p represents the decision-makers' concern with respect to the maximal deviation (Fattahi & Fayyaz, 2010).

The solution with the lowest $L_p(x)$ value is the best compromised solution among the alternatives as it corresponds to the nearest distance to the ideal point. Obviously, depending on the values of weight w_i and parameter p, the best compromised solution is likely to change. With different values of these parameters, a sensitivity analysis can be carried out to form best-suited sets depending upon the decision-maker preferences.

The MOOP model is transformed to a CP model called $CP1$ as follows by Equation (16) and (17);

$CP1$:

$$min \;\; L_p(x) = \left\{ W_1^p \left[\frac{(\sum_{i=1}^{s} x_i \, c_i) - C^*}{C' - \, C^*} \right]^p + \; W_2^p \left[\frac{(\sum_{i=1}^{s} x_i \, P_i) - P^*}{P' - \, P^*} \right]^p + \; W_3^p \left[\frac{R^* - \left(\prod_{i=1}^{s} \sum_{j=k_i}^{k_i+x_i} \binom{k_i+x_i}{k_i} R_i^j (1-R_i)^{k_i+x_i-j} \right)}{R^* - \, R'} \right]^p \right\}^{1/p} \quad (16)$$

$$st.Eq \; (6) \; - \; (10) \quad (17)$$

where C^* and C' are ideal and anti-ideal values, P^* and P' are ideal and anti-ideal values of power consumption, R^* and R' are ideal and anti-ideal values of reliability, and W_1 , W_2 and W_3 are the weights of cost, power consumption and reliability objectives.

It is known that the largest deviation *d* among the individual deviations is minimized as $p \rightarrow \infty$. The largest deviation is considered for $p = \infty$ where $L_p(x)$ represent the Chebycheff metric, and the problem becomes the $min/\max problem$ shown in $CP2$ model by Equation (18) and (22);

$CP2$:

$$\min \; L_\infty = d \quad (18)$$

$$st. \; W_1 \frac{(\sum_{i=1}^{s} x_i \, c_i) - C^*}{C' \; - \; C^*} \; \leq d \quad (18)$$

$$W_2 \frac{(\sum_{i=1}^{s} x_i \, P_i) - P^*}{P' - \, P^*} \leq d \quad (19)$$

$$W_3 \frac{R^* - \left(\prod_{i=1}^{s} \sum_{j=k_i}^{k_i+x_i} \binom{k_i+x_i}{k_i} R_i^j (1-R_i)^{k_i+x_i-j} \right)}{R^* - R'} \leq d \tag{20}$$

$$Eq\ (6) - (10) \tag{22}$$

4. Simulated Annealing

The SA algorithm is inspired by the annealing method used in metallurgy, which involves heating and controlled cooling to change a material's physical properties. The SA method is widely used to solve different types of integrated optimization problems based on an iterative probabilistic search technique. It was first proposed by (Metropolis, Rosenbluth, Rosenbluth, Teller, & Teller, 1953), and later introduced as an iterative optimization method by (Kirkpatrick, Gelatt, & Veechi, 1982). The SA algorithm is a meta-heuristic method that successfully solves difficult problems (Murray & Church, 1996).

In this study, we used the SA algorithm presented in Figure 2. The SA algorithm starts with a temperature value determined as the initial temperature T_0. An initial solution generated with random variables constitutes the first and also the current solution. The objective function value of the initial solution becomes the fitness value of the current solution and the best solution. After evaluating the current solution, a neighbor solution is created by using the defined neighbor generation steps presented in Figure 3. If the fitness value of the neighborhood solution is better than the fitness value of the current solution, the current solution becomes the neighborhood solution. Otherwise, the neighborhood solution is accepted or rejected depending on the value of the acceptance probability. The acceptance probability is calculated by Equation (23):

$$P = exp\,(-\Delta E/T) \tag{23}$$

where ΔE is the difference in energy (or value of the objective function) between the current solution and the proposed solution, and T is the current temperature, which decreases over time. The temperature controls the randomness of the algorithm, and as it decreases, the acceptance probability becomes smaller, causing the algorithm to be more selective in accepting proposed solutions. At high temperatures, the acceptance probability is high, allowing for more exploration and randomness in the search space. At low temperatures, the acceptance probability is low, allowing for more exploitation and refinement of the current solution.

The optimal cooling schedule, including the initial temperature and cooling rate, is chosen meticulously to ensure that the algorithm converges to the global optimum. The temperature is gradually reduced by a cooling parameter at each iteration until the predetermined final temperature is reached. We set the initial temperature to 1000 and the final temperature to 0. The cooling rate is selected as 0.98 by trial and error.

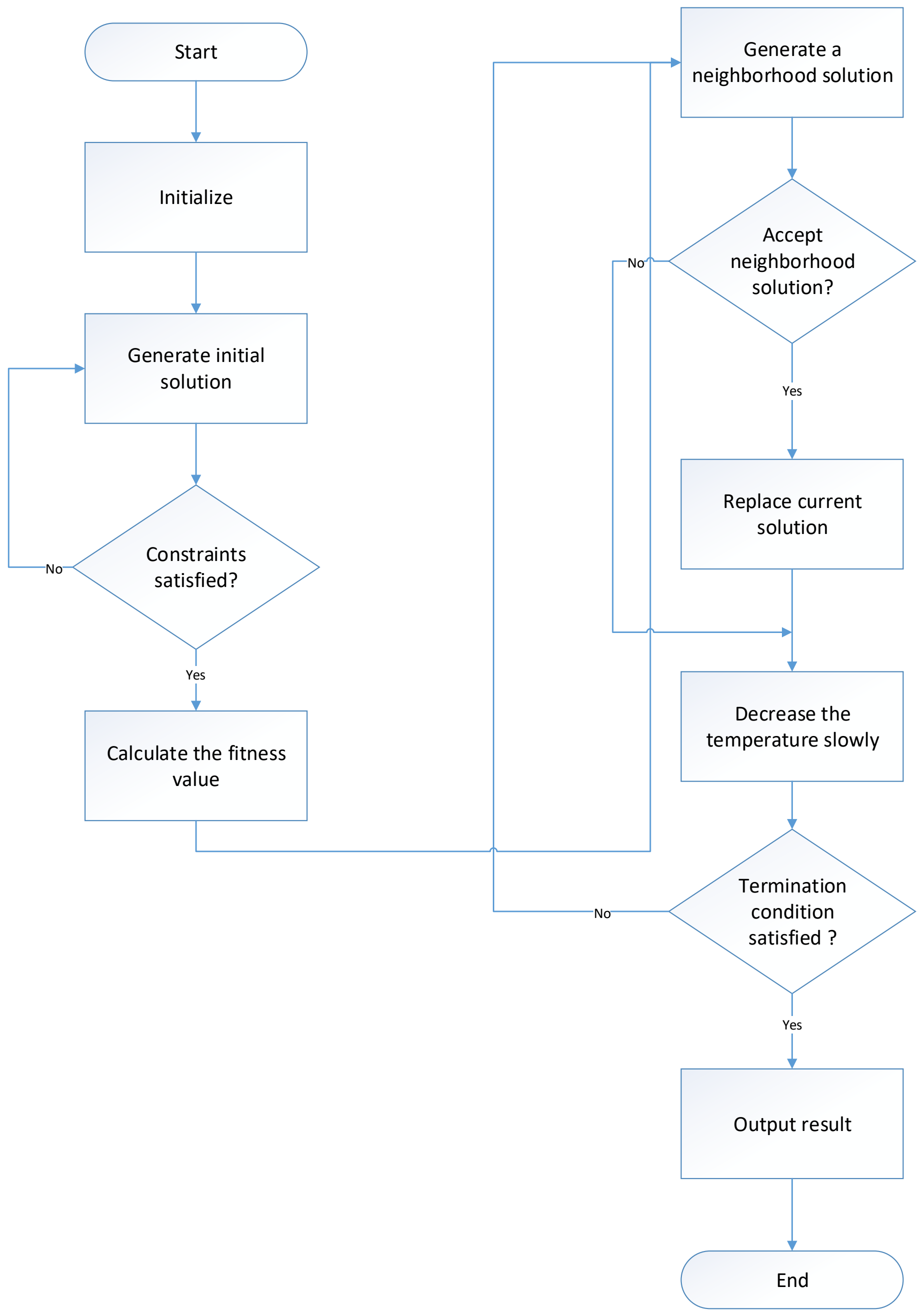


Figure 2: The SA Algorithm

To generate neighborhood solutions, we follow the steps presented in Figure 3. We defined a single dimensional array whose dimension is equal to the number of subsystems. Then, an initial solution is generated randomly by assigning various redundant units to each subsystem. To generate a neighborhood solution, we first generated two random floating-point numbers between [0,1]. Depending on the value of the first random number, a relevant subsystem is selected. Then, depending on the value of the second random number we either increased or decreased the number of redundant units by one. We have coded the SA algorithm in Python and run the algorithm in an Intel Core i5.

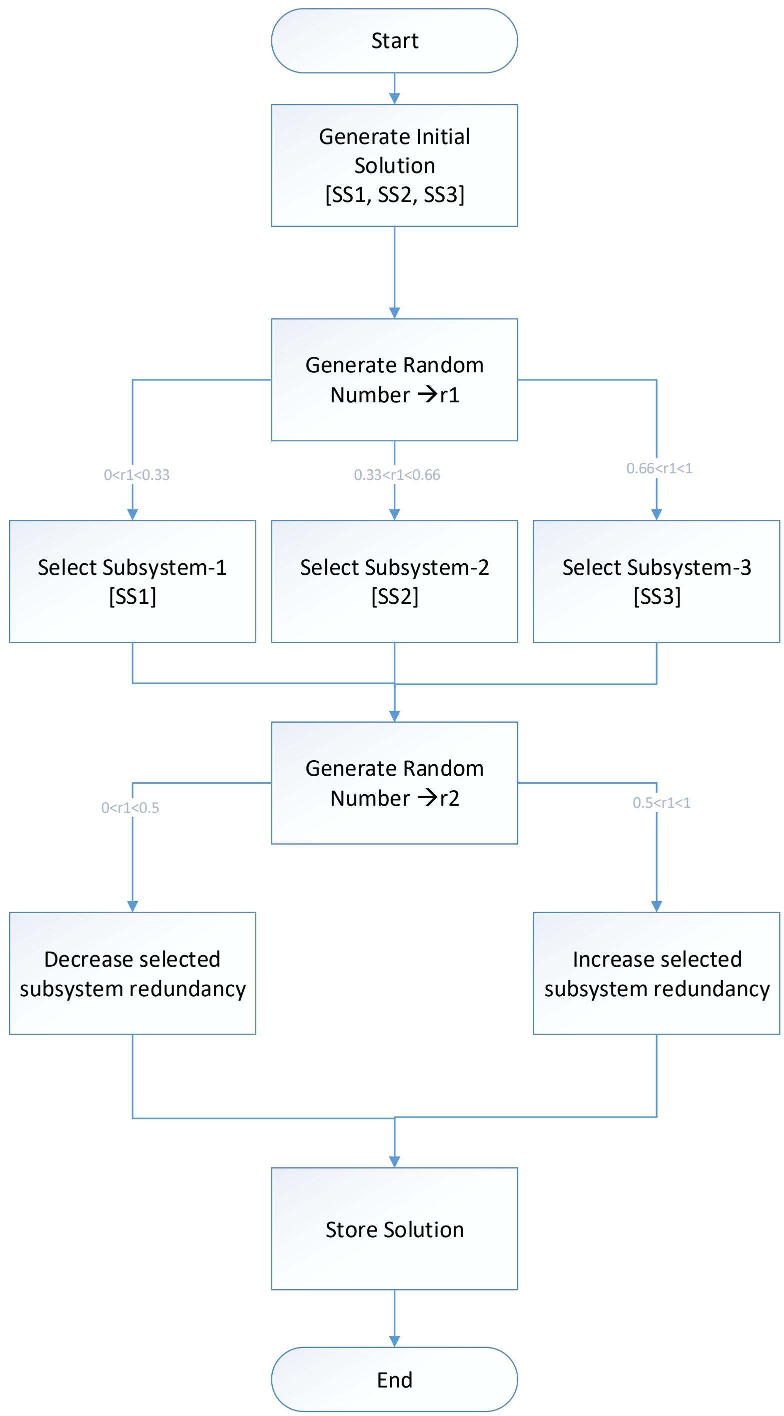


Figure 3: Problem-Specific Neighbor Solution Generation Algorithm

Before dealing the presented model, we test the performance of the SA algorithm on the following single objective model in which the aim is to minimize the cost of redundant units in the system.

$$min \quad Z = g(x) = \sum_{i=1}^{s} x_i \, c_i \tag{24}$$

$$st. \quad \prod_{i=1}^{s} \sum_{j=k_i}^{k_i+x_i} \binom{k_i + x_i}{k_i} R_i^j (1 - R_i)^{k_i+x_i-j} \geq R_{\text{sys\_min}} \tag{15}$$

$$\sum_{i=1}^{s} x_i \leq n_{\max} \tag{26}$$

$$n_i^{\mathrm{l}} \leq x_i \leq n_i^{\mathrm{u}}, \qquad \forall i \tag{27}$$

$$\sum_{i=1}^{s} x_i \, P_i \leq P_{red} \tag{28}$$

$$x_i \geq 0 \; and \; integer \tag{29}$$

However, the above introduced model is still nonlinear and cannot be solved by solvers like GAMS. Therefore, we have transformed this model into a simpler nonlinear model. The revised model selects among the set of configurations with known reliability score instead of the number of redundant units. Reliability scores of each subsystem is calculated by considering various possible redundant units in a subsystem. Then, we selected the configurations for each subsystem that provides the lowest cost. The resultant model can be solved using GAMS Dicopt Solver. When we compared the results obtained with that of the SA algorithm, we realized that both approaches yield the same result. Moreover, SA algorithm reached even alternative optima for the same problem. Although we can not share the results of this problem due to space restrictions, this analysis indicates the contribution of a metaheuristic algorithm like SA.

We should also point out that since our search space is relatively small, we believe that many available meta-heuristic algorithms are capable to solve this model. Although our search space is relatively small, the nonlinear nature of our problem requires the use of a metaheuristic algorithm. As one of the options, SA is suitable in this sense.

5. Computational Results

In order to demonstrate the performance of the proposed model, a case study for a large-size communication satellite is carried out. The selected payload subsystem configurations presented in Section 3, namely the redundancy schemes of the Mission-1, the Mission-2 and the Mission-3 subsystems, are configured as a $k\ out\ of\ n$ redundant system. These subsystems are being demonstrated for different payload missions in different frequency bands to dedicated applications in a typical communication satellite. The reliability figures of the units are derived from actual failure-in-time (FIT) values from the satellite industry practices. Moreover, the number of units in a subsystem are taken to be very close to those used in a typical large-size communication satellite with respect to the current market trends. For the M-1 subsystem, from 32:33 to 32:48 payload channel configurations are considered. That is, a maximum of 16 redundant units can be used in this subsystem. Similarly, for the M-2 subsystem, 16:17 to 16:26 payload channel configurations, and for the M-3 subsystem, 10:11 to 10:18 configurations are considered. Table 1 gives the associated cost, power consumption and reliability values of the units for each mission on the satellite model.

Table 1: Input Parameters of the Satellite Model

Value per Equipment	**Subsystem**		
	M-1	M-2	M-3
Cost (million USD)	0.750	0.850	0.800
Power Consumption (Watt)	1	50	40
Equipment Reliability	0.8826	0.8943	0.8884
Min. Required Reliability	0.90	0.95	0.92
Redundancy Strategy	Warm-Standby	Hot-Standby	Hot-Standby

As explained in Section 4, the parameters w_i are the weights corresponding to the relative significance of the i^{th}objective from the perspective of the decision maker. By using various sets of weights, the method allows addressing different types of satellite mission. In our case study, two types of satellites, called Satellite-A in the commercial satellite domain and Satellite-B in the governmental/military mission domain are designated with the associated weights defined by expert judgments.

The weighting strategy used in the CP1 and CP2 models for both satellite types are given in Table 2. For commercial satellite cases, cost efficiency is relatively more important than the other objectives since return on investment for such a significant project is always in the foreground. Therefore, the weight of the cost is larger than the other objectives for a commercial satellite. On the other hand, for a governmental/military satellite, higher reliability is much preferable as compared to less cost, since, in general, the mission of the satellite is related to strategic needs where failures are not tolerable. It is worth noting at this point that while the objectives are very different, the scaling in Eq. (15) allows using comparable weights summing up to 1.

Table 2: Weighting Strategy of the Model CP1 and CP2

$\mathbf{W_i}$	Satellite-A	Satellite-B
$\mathbf{W_1}$	0.1	0.6
$\mathbf{W_2}$	0.1	0.2
$\mathbf{W_3}$	0.8	0.2

When the MOOP model is run by considering each objective function separately, the following pay-off table is obtained in Table 3. The diagonal elements show the value of the objective functions whereas the others show the value of corresponding objectives.

Table 3: Pay-off Between the Objectives

		Minimum cost	**Minimum power consumption**	**Maximum reliability**	**Ideal point**	**Anti-ideal point**
Cost (million USD)		13.45	14.90	22.25	13.45	22.25
Power consumption (watt)		418	410	742	410	742
Reliability		0.945	0.9404	0.9994	0.9994	0.9450
Number of redundant equipment per subsystem	M-1	8	10	12		
	M-2	5	4	9		
	M-3	4	5	7		

Table 3 clearly indicates the degrees of conflicts between the objectives. When the cost is minimized, an alternative design is obtained with 13.45 million USD having a power consumption of 418 watts and a reliability value of 0.945. On the other hand, when the power consumption is minimized, an increase in the cost (from 13.45 to 14.90 million USD) is observed and a decrease in reliability occurs. When the reliability is maximized, we observe a 65% increase in cost (from 13.45 to 22.25 million USD), and an 81% increase in power consumption (from 410 to 742 watts) as compared to the case where the cost is minimized. In this case, the decrease in reliability remains somehow limited at 5.4% (from 0.9994 to 0.945). In our case the ideal solution is the point where the cost is 13.45 million dollars, the power consumption is 410 watt and, the reliability is 0.9994 as indicated in Table 3. Such an approach is expected to prove effective in the presence of the large degrees of conflicts as illustrated above.

We solve the model CP1 with p $values$ of 1 and 2 and also solve the model CP2. The results are given in Table 4 and Table 5 for Satellite-A and Satellite-B, respectively.

Table 4: Results for Satellite A

Model	p	Cost (Million USD)	Power Consumption (Watt)	Reliability	Number of Redundant Equipment Per subsystem		
					M-1	M-2	M-3
CP1	1	19.75	602	0.9969	12	7	6
	2	19.00	601	0.9962	11	7	6
CP2	∞	19.00	601	0.9962	11	7	6

Table 5: Results for Satellite B

Model	p	Cost (Million USD)	Power Consumption (Watt)	Reliability	Number of Redundant Equipment Per subsystem		
					M-1	M-2	M-3
CP1	1	13.45	418	0.9450	8	5	4
	2	14.20	419	0.9585	9	5	4
CP2	∞	15.00	459	0.9689	9	5	5

Depending on the weighting strategy used in the CP1 and CP2 models, alternative redundant equipment configurations are attained. For Satellite-A which is developed for governmental/military cases, a solution with a higher reliability and therefore a higher cost is obtained. On the other hand, for Satellite-B which demonstrates commercial prospects, a low cost solution that satisfies the minimum reliability requirement is obtained. This was an expected outcome since for commercial satellites cost parameter is generally more prominent than the reliability. Figure 4 depicts the results of the MOOP for Satellite-A and Satellite-B along with the ideal and anti-ideal points in a consolidated graph. The solution obtained for Satellite-A can be seen on the upper range of high reliability, cost and power consumption zone, whereas the solution for Satellite-B is on the lower side of the graph in a relatively low reliability, cost and power consumption zone. Ideal and anti-ideal points are situated at the extreme corners of the graph.

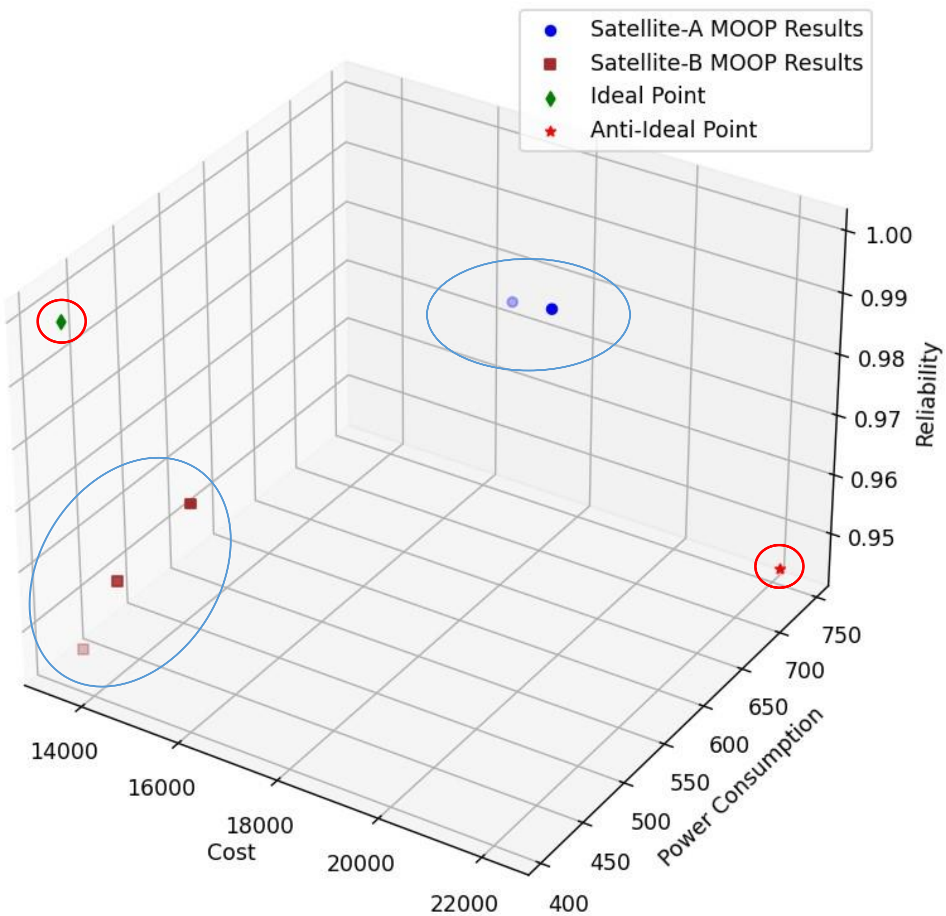


Figure 4: MOOP Results of Satellite-A and Satellite-B

In Table 6, changes on cost, power consumption and reliability with respect to the various cases are given for sensitivity analysis.

In order to analyze the sensitivity of the CP1 and CP2 models against various weight sets and p-values, each model was run by six weight sets and p values of 1,2 and infinity. The obtained results are given in Table 6. The computational time for each trial was between 50-60 seconds.

Table 6: Sensitivity Analysis of CP1 and CP2 for various weights and p-values

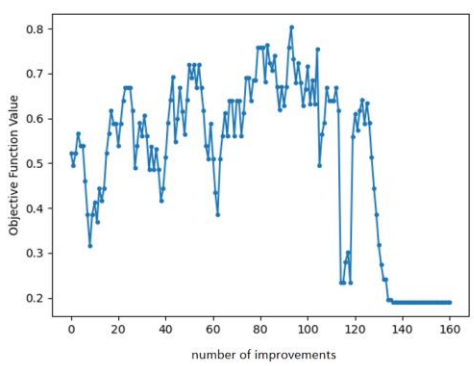
Trial	p	Weight Sets			Cost (Million USD)	Power Consumption (Watt)	Reliability	Number of Redundant Equipment		
		W_1 (cost)	W_2 (power consumption)	W_3 (reliability)				M-1	M-2	M-3
1	1	0.1	0.1	0.8	19.75	602	0.9969	12	7	6
2		0.2	0.2	0.6	17.35	511	0.9891	11	6	5
3		0.33	0.33	0.34	14.95	420	0.9640	10	5	4
4		0.6	0.2	0.2	13.45	418	0.9450	8	5	4
5		0.7	0.2	0.1	13.45	418	0.9450	8	5	4
6		0.8	0.1	0.1	13.45	418	0.9450	8	5	4
7	2	0.1	0.1	0.8	19.00	601	0.9962	11	7	6
8		0.2	0.2	0.6	17.35	511	0.9891	11	6	5
9		0.33	0.33	0.34	15.85	509	0.9813	9	6	5
10		0.6	0.2	0.2	14.20	419	0.9585	9	5	4
11		0.7	0.2	0.1	14.20	419	0.9585	9	5	4
12		0.8	0.1	0.1	13.45	418	0.9450	8	5	4
13	∞	0.1	0.1	0.8	19.00	601	0.9962	11	7	6
14		0.2	0.2	0.6	17.45	560	0.9891	10	7	5
15		0.33	0.33	0.34	15.85	509	0.9813	9	6	5
16		0.6	0.2	0.2	15.00	459	0.9689	9	5	5
17		0.7	0.2	0.1	14.20	419	0.9585	9	5	4
18		0.8	0.1	0.1	14.20	419	0.9585	9	5	4

While same weights are used, the distance to the ideal solution decreases as the p-value increases. Similarly, as the weights for each objective changed, the obtained results change in most of the cases. When p is set to 1 and the weight of the cost objective is increased gradually, the cost changes in 4 out of 6 trials.

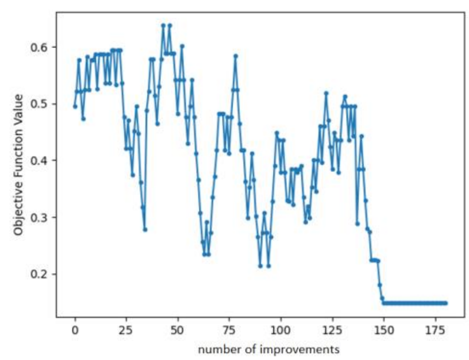
Compared to trial 1 and 2 tested above for different types of satellites, we obtain a completely different redundancy policy when we set weights almost equal to each other in trial 3. As it is clear from the results change in reliability score results in huge savings measured in millions.

When p-value is set to 2 and the weight of the cost objective is increased gradually, solutions with higher reliability compared to the first case is obtained. When the result of the trial 9 with equal weights is compared to trial 3, we obtain a better result in terms of reliability. However, this improvement in reliability is due to the increase in cost and sharp increase in power consumption. On the other hand, setting p-value to infinity resulted in some minor changes in the obtained results compared to the second case.

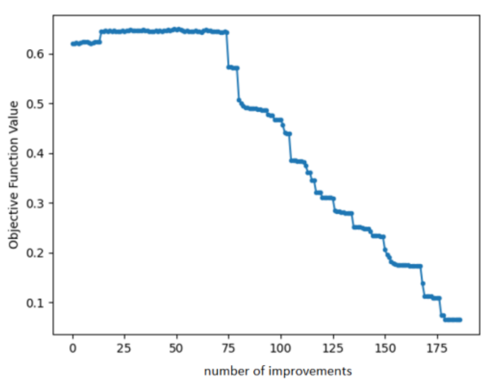
Considering the large number of iterations we observed, we believe that the algorithm converges to an optimal -or at least a near-optimal- solution. The convergence graphs obtained for various values of W and p, are presented in Figure 5. These graphs show that the algorithm converges to the same value for different runs. As the aim of the CP is to minimize the distance to the utopia point, we can say that we are very close to this point since our fitness function value is close to 0.



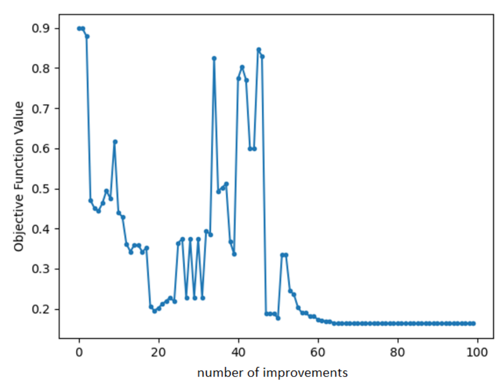
Satellite A p:1 W_1:0,1-W_2:0,1-W_3:0,8



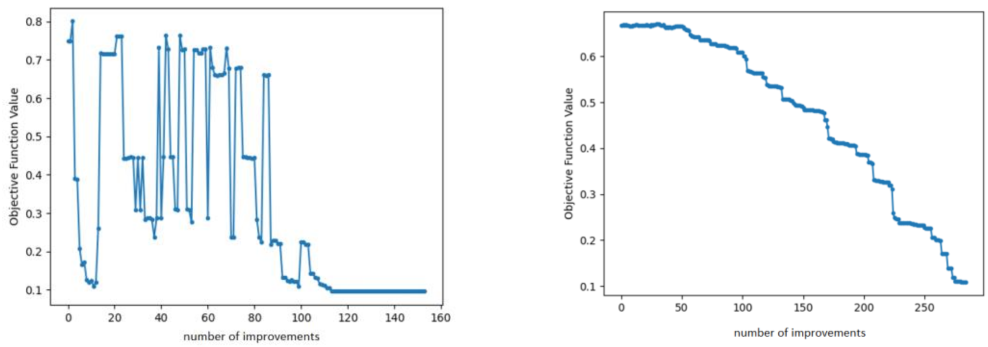
Satellite -A p:2 W_1:0,1-W_2:0,1-W_3:0,8



Satellite -A p:∞ W_1:0,1-W_2:0,1-W_3:0,8



Satellite -B p:1 W_1:0,6-W_2:0,2-W_3:0,2



Satellite -B p:2 W_1:0,6-W_2:0,2-W_3:0,2 Satellite -B p: ∞ W_1:0,6-W_2:0,2-W_3:0,2

Figure 5. Convergence graphs for some weights

6. Conclusion

In this study, we use a MOO approach to the design of a communication satellite payload by considering system reliability, power consumption of the units and the cost of the satellite concurrently, which are conflicting objectives by their nature. The CP method has been utilized as a MOO technique and we proposed CP models for the satellite design problem. These models are solved using SA algorithm since these models contain nonlinear constraints. By using two sets of weights in the CP model, commercial and defense domains are addressed.

The proposed approach facilitated trade-off studies between objectives of minimization of cost and maximization of reliability while trying to minimize power consumption of active units in the early design phase of satellite. Since the resources are limited onboard in space, defined constraints are taken into consideration in the model. The results implied that substantial cost saving could be possible in the expense of slight relaxation on the reliability value. It is believed that the proposed methodology would pave the way for an effective sensitivity analysis of satellite payload and reliability design.

This study is the first systematic treatment for the optimization of the satellite design in the scientific literature. Our aim is to determine the best redundancy strategy by considering conflicting objectives and onboard constraints. The proposed method enables the optimization of the reliability of a satellite system which includes quite expensive redundant active and warm standby units. The offered methodology could likewise be implemented for complex non-repairable systems in various industrial domains such as chemical plants, nuclear systems, power generation systems, oil and gas refineries, aerospace industries and large-scale compound manufacturing plants. Additionally, the proposed model allows expanding the scope of the problem formulation by incorporating additional design constraints specific to satellite systems.

These constraints could include factors such as weight limitations, communication bandwidth requirements, thermal constraints, and operational constraints.

One shortcoming of the proposed approach is that the SA algorithm does not guarantee an optimal solution; however, it is expected to produce near-optimal solutions at worst, as discussed before. Also, using classical optimization methods for solving the nonlinear integer program would not guarantee an optimal solution and would take too long to solve. The proposed approach demonstrated that there are significant trade-offs among cost, power consumption that can be taken advantage of by using systematic MOO approach in the early design phase of satellites. For instance, for satellite A, the MOO achieved a reliability value of 0.996 with a cost of $19 million and a power consumption of 601 watts. In contrast, a single objective maximization of reliability will achieve only a slightly increased reliability value of 0.9994 but at the cost of $22.25 million and 704 watts.

The Multi-Objective Optimization (MOO) approach, incorporating considerations of system reliability, power consumption, and cost concurrently, enables a more holistic and informed decision-making process. Decision makers should recognize the interconnectedness of these objectives and adopt a comprehensive optimization strategy. The proposed approach demonstrated the potential for achieving significant cost savings by accepting a slight relaxation in reliability values. Decision-makers should weigh the cost implications against the incremental gains in reliability, recognizing that optimizing for both objectives may lead to more cost-effective solutions. The proposed methodology would pave the way for an effective sensitivity analysis of satellite payload and reliability design. In essence, the study provided a foundation to make informed decisions in the early design phase of satellites, optimizing conflicting objectives and navigating resource constraints effectively. The proposed methodology opens avenues for broader application across industries, emphasizing the strategic advantages of a systematic MOO approach in achieving cost-effective and reliable solutions.

Future research could focus on uncertainties inherent in satellite system design such as component failure rates or environmental factors. To address these uncertainties, advanced modeling techniques, such as stochastic programming could be employed. Also. the proposed approach could be implemented for complex non-repairable systems in various industrial domains such as chemical plants as indicated in the conclusion section. Future research may involve such applications modeling new MO objective functions and additional domain-specific constraints.

Acknowledgments

The authors are thankful to the anonymous reviewer(s) for providing valuable comments and suggestions that enable substantial improvement of the quality of this article.

Statements and Declarations

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. The authors have no competing interests to declare that are relevant to the content of this article.

Ethical Statement

Hereby, we consciously assure that for the manuscript “A Multi-Objective Perspective to Satellite Design and Reliability Optimization” the following is fulfilled:

1) This material is the authors' own original work, which has not been previously published elsewhere.

2) The paper is not currently being considered for publication elsewhere.

3) The paper reflects the authors' own research and analysis in a truthful and complete manner.

4) The paper properly credits the meaningful contributions of co-authors and co-researchers.

5) The results are appropriately placed in the context of prior and existing research.

6) All sources used are properly disclosed (correct citation). Literally copying of text must be indicated as such by using quotation marks and giving proper reference.

7) All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

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